

Score-based Generative Modeling in Latent Space

Year: 2021 | Citations: 793 | Authors: Arash Vahdat, Karsten Kreis, Jan Kautz

Abstract

Score-based generative models (SGMs) have recently demonstrated impressive results in terms of both sample quality and distribution coverage. However, they are usually applied directly in data space and often require thousands of network evaluations for sampling. Here, we propose the Latent Score-based Generative Model (LSGM), a novel approach that trains SGMs in a latent space, relying on the variational autoencoder framework. Moving from data to latent space allows us to train more expressive generative models, apply SGMs to non-continuous data, and learn smoother SGMs in a smaller space, resulting in fewer network evaluations and faster sampling. To enable training LSGMs end-to-end in a scalable and stable manner, we (i) introduce a new score-matching objective suitable to the LSGM setting, (ii) propose a novel parameterization of the score function that allows SGM to focus on the mismatch of the target distribution with respect to a simple Normal one, and (iii) analytically derive multiple techniques for variance reduction of the training objective. LSGM obtains a state-of-the-art FID score of 2.10 on CIFAR-10, outperforming all existing generative results on this dataset. On CelebA-HQ-256, LSGM is on a par with previous SGMs in sample quality while outperforming them in sampling time by two orders of magnitude. In modeling binary images, LSGM achieves state-of-the-art likelihood on the binarized OMNIGLOT dataset. Our project page and code can be found at <https://nvlabs.github.io/LSGM>.